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A Robust-Resistant Approach to Interpret Spatial Behavior of Saturated Hydraulic Conductivity of a Glacial Till Soil Under No-Tillage System

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A central Iowa glacial till soil under no-tillage condition was studied for its spatial behavior of saturated hydraulic conductivity (K) at the surface soil layers. Hydraulic conductivity measurements both in situ and in the laboratory were made at two depths of 15 and 30 cm at regular intervals of 4.6 m on two perpendicular transects crossing each other at the center of the field. Simplified split-window median polishing in conjunction with a robust semivariogram estimator were used to examine the spatial structure of the glacial till material. Results of this study indicated a nested structure of K at 30 cm depth. Soil clustering at the experimental site at intervals of 20 m, in addition to the soil microheterogeneity, contributed to variation in K, with an overall range of spatial dependence of K up to 60 m. Medians of split windows of 23 m width were found to be the "solo representatives" or "summary points" of the soil clusters contributing to spatial structure. In situ and laboratory measurements for K showed consistency in their trends even though some parametric variations were observed. K values observed near the soil surface at a depth of 15 cm were dominated by white noise and directional trends.

INTRODUCTION

Glacial deposits have often been regarded as one of the most variable and complex geological materials [*Terzaghi and Peck*, 1967]. *Dreimanis* [1976] and *Lutenegger et al.* [1983] concluded that the influence of genesis on various properties of till and diamiction materials occurs primarily as a result of gross differences in depositional environment and that supraglacial deposits are highly variable compared with basal till. These researchers determined that the postdepositional changes in glacial deposits can produce a complex set of effects on the behavior of the till soil. Moreover, recent studies indicate that preferential flow paths and spatial variability in hydraulic conductivity (K) of the soil have significant influence on chemical transport from agricultural fields to shallow groundwater [*Kanwar et al.*, 1988, 1990*a*, *b*]. *Sharma et al.* [1987] demonstrated that subsurface flow can be increased with increased spatial dependence in the hydraulic properties of the soil. Therefore more accurate characterization and quantification of K variability are needed to make reasonable estimates of water and chemical recharge rates to groundwater systems from glacial till agricultural watersheds.

Field experiments were conducted to study the spatial structure of K in a glacial till material in central Iowa, employing exploratory techniques and (robust) geostatistics. After appropriate scale transformations of measured K data were calculated using constant head and Guelph permeameters [*Klute*, 1965, *Reynolds and Elrick*, 1986], robust semivariograms were computed for two soil depths. A resistant approach of "split-window median polish" across transects was used to examine the appropriateness of the semivariograms. The main objective of this study was to examine the variability and the dependence of K on sampling distance, that is, minimum (optimum) number of representative samples to be analyzed to characterize K on a field scale. The second objective was to estimate and interpret semivariograms as a measure of continuity or autocorrelation of K for the glacial till material. The third objective was to observe the effect of soil depth on K variability. In addition to these objectives, consistency in semivariograms using two measuring techniques was also compared.

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PREVIOUS APPLICATION

The geostatistical approach of using semivariograms [*David*, 1977; *Journel and Huijbregts*, 1978; *Clark*, 1979] to evaluate the spatial structure of soil properties has become increasingly popular. Several scientists in the last decade have devoted their attention to the spatial distribution of physical, chemical, and hydrogeological properties of soils. *Gajam et al.* [1981], *Russo and Bresler* [1982], *Vauclin et al.* [1982], *Yost et al.* [1982], *Russo* [1984], *Oliver and Webster* [1986] and others used geostatistical estimators to determine the spatial structure of different soil properties. *Webster* [1985] summarized the various geostatistical tools available in the area of soil science. *Onofiok* [1988] studied spatial and temporal variability of some tillage-induced soil physical properties of a Nigerian paleustult and found significant differences in soil macroporosity and K values due to tillage and date of sampling. Although most of these researchers used the basic assumptions needed for geostatistical analysis, they usually failed to examine whether the data measured in the field satisfied these assumptions [*Horowitz and Hillel*, 1983; *Hamlett et al.*, 1986; *Cressie and Horton*, 1987]. Various studies by *Cressie* [1984, 1986], *Cressie and Hawkins* [1980], *Cressie and Glonek* [1984], *Hamlett et al.* [1986], and *Cressie and Horton* [1987] have introduced resistant and exploratory data analysis techniques such as effects of drift, robust variogram estimation, and robust kriging to geostatistical analysis.

Techniques reported by *Tukey* [1977] for performing exploratory analyses could be adopted to characterize the spatial structure of soil properties. This paper demonstrates how the soil hydraulic conductivity data taken at spatial locations and arranged on a regular "cross" (i.e., two transects intersecting each other at the center of the field at an angle of 90°) can be analyzed with exploratory data analysis techniques when nonstationarity is the inherent property of most of the soils [*Hamlett et al.*, 1986].

Theoretical Background for Spatial Analysis

Matheron [1963] proposed the technique of "Geostatistics" for spatial analysis of ore reserves from sampled data whose relative spatial locations were known. *David* [1977], *Journel and Huijbregts* [1978], and *Clark* [1979] have addressed this problem and presented case studies in the field of mining.

Experimental variograms are the main tools used to explore the spatial structure of soil properties in the field. Because these semivariograms can provide the basis for further geostatistical assessment of soil properties, accurate analysis of data is needed before developing semivariogram or kriging maps [*Hamlett et al.*, 1986]. A brief theory of geostatistics is reviewed, with attention paid to crucial stationarity assumptions.

Assuming that $Z(x)$, a regionalized variable where (x) denotes a location in the space domain (Γ), is the random measurement of the case-specific soil property taken at location (x), two types of stationarities are typically assumed that $Z(x)$ may satisfy. $Z(x)$ is said to be stationary of order 2 (i.e., second-order stationarity) if (1) $E\{Z(x)\} = m$, for any x, which states that the expected value of the random function in space exists and does not depend on location x, and (2) $E\{Z(x + h) \cdot Z(x)] - m^2\} = C(h)$ for any x and h, which states that for each pair of variables $\{Z(x + h), Z(x)\}$ the covariance function $C(h)$ exists and does not depend on location but only on the separating vector h [*Journel and Huijbregts*, 1978, p. 32]. The less demanding intrinsic hypothesis by *Matheron* [1963] makes the following stationarity assumptions, which are expressed entirely in terms of differences $\{Z(x + h) - Z(x)\}$ of the regionalized variable: (1) $E\{Z(x + h) - Z(x)\} = 0$, for any x and h; in other words, one expects $Z(x)$ to be constant for any x and h in Γ, and (2) $2\gamma(h) = E\{[Z(x + h) - Z(x)]^2\}$, for any x and h, where $\gamma(h)$ is a semivariogram estimator which states that variance of the difference in soil property depends only on the separating vector h. Thus second-order stationarity implies the intrinsic hypothesis, but the reverse is not true. Following *Matheron* [1963], *Journel and Huijbregts* [1978] and *Burgess and Webster* [1980] studied spatial variability using semivariograms and defined an average semivariogram $\bar{\gamma}(h)$ in a specific direction as

$$\bar{\gamma}(|h|, \alpha) = [1/2N(|h|, \alpha)]\left\{\sum_{i=1}^{N} [Z(x_{i+|h|}) - Z(x_i)]^2\right\}, \tag{1}$$

where $\bar{\gamma}(|h|, \alpha)$ is a semivariogram estimator, α implies direction, $|h|$ is modulus of interval, N is the number of pairs having a specified separating vector, and $Z(x_i), \cdots, Z(x_n)$ are soil property data taken at field locations $x_i, \cdots, x_n$. *Journel and Huijbregts* [1978, pp. 175 and 262] reported that semivariograms may be directionally dependent and that data can be checked for anisotropy by computing $\bar{\gamma}(|h|, \alpha)$ for different α. Note that for field data the separation vector $(|h|, \alpha)$ would present a range of values rather than a particular value.

Unfortunately, the field data of many soil properties generally contain some outliers that can obscure the whole $\bar{\gamma}(h)$ estimation by increasing the variance. Among many others, *Cressie and Hawkins* [1980] proposed a modified estimator, known as a robust estimator, suitable to curtail the effect of these outliers by downweighting and defined as

$$\bar{\gamma}(|h|, \alpha) = \frac{\left\{[1/2N(|h|, \alpha)] \sum_{i=1}^{N} [Z(x_{i+|h|}) - Z(x_i)]^{1/2}\right\}^4}{0.457 + 0.494/N(h) + 0.045/N(h)^2}. \tag{2}$$

Journel and Huijbregts [1978] have reported that the observed variability of a phenomenon is most often due to the presence of microstructures within macrostructures, sampling variation, and so forth. When all structures of variability come into play simultaneously and for all distances h, they are called nested structures. The overall variogram $\gamma(h)$ for the nested structure can be written as [*David*, 1977, p. 123; *Journel and Huijbregts*, 1978, p. 150]

$$\gamma(h) = \gamma_1(h) + \gamma_2(h) + \cdots + \gamma_n(h), \tag{3}$$

where $\gamma_1(h), \cdots, \gamma_n(h)$ are the variograms of the components contributing to the spatial structure.

For the sake of completeness we may describe a few of the theoretical models encountered most commonly in practice, including that of this study. The spherical model [*Clark*, 1979] in isotropic form can be written as

$$\begin{aligned} \gamma(h) &= C_0 + C_s[(3h/2A) - (h^3/2A^3)] \qquad 0 < h \le A \\ \gamma(h) &= C_0 + C_s = C \qquad h > A, \end{aligned} \tag{4}$$

where C_0 is the nugget component, C_s is the spherical component, C is the sill, and A is the range of the semivariogram. The spherical model is one of the most common transitive models to fit soil properties data. Another model that has also been used is the exponential model:

$$\gamma(h) = C_0 + C_e[1 - \exp(-h/A)] \qquad 0 < h \le d, \tag{5}$$

where C_e is the exponential component and d (e.g., $d > 3A$) is the maximum distance over which the semivariogram is defined. Unlike the spherical model, the exponential model reaches the sill asymptotically. Both spherical and exponential models show linear behavior at the origin.

The parameters of the theoretical variograms matching the experimental variograms can be identified using kriging by the jack-knifing approach [*Vauclin et al.*, 1983]. The parameters can then be validated with the criteria proposed by *Gambolati and Volpi* [1979]. *Springer and Cundy* [1987] referred to these criteria as kriged average error (KAE), kriged reduced mean square error (KRMSE), and kriged mean square error (KMSE). Furthermore, the kriged value

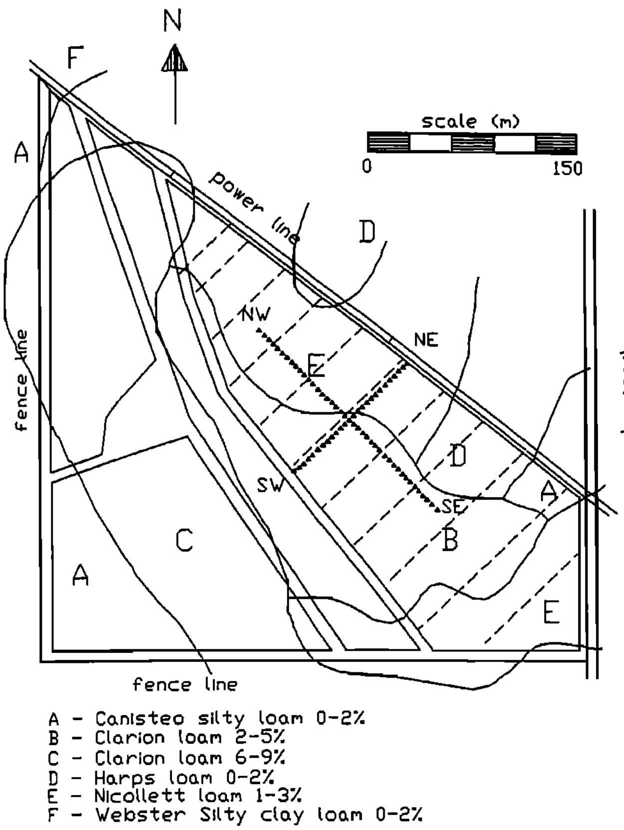


Fig. 1. Experimental plot for spatial study of K in Boone county, Iowa; 66 sampling sites arranged on two transects (NE-SW and NW-SE) across the field (soil type map included). Triangles indicate sampling sites.

should be positively correlated with the observed value of the regionalized variable. Finally, the theoretical variogram model (of raw data or drift residuals) should closely approximate the observed variogram of the raw data or of the residuals [*Journel and Huijbregts*, 1978, p. 167 and 246]. Ordinary and universal kriging computations were performed with a computer routine adopted from the United States Geological Survey [*Grundy and Miesch*, 1987].

EXPERIMENTAL METHODS

A 115 m × 183 m experimental plot was used for this study at the Agronomy and Agricultural Engineering Farm near Boone in central Iowa. Soil types in this plot were Nicollet loam and Clarion loam derived from glacial till. The plot had gentle slopes of less than 2% on the north and was on a slightly convex rise on the south with low relief [*U.S. Department of Agriculture*, 1984]. It has also been under no-tillage management for the last 6 years. A Guelph permeameter [*Reynolds and Elrick*, 1986] was used to measure the in situ values of K at sites located on two perpendicular transects crossing at the center of the field. The transects were oriented in NW-SE and NE-SW directions along the major and minor axes of the field and are shown in Figure 1. This type of sampling pattern is not commonly used to study the spatial dependence of soil hydraulic properties. The design was intended to limit the number of K measurements and to generate sufficient number of pairs at intermediate lag distances. The sampling pattern also provided an adequate number of pairs for directional geostatistical analysis and for exploratory data analysis in NW-SE and NE-SW directions.

K measurements with the Guelph permeameter were made at 4.6-m intervals on both transects, at 15 and 30 cm depths. This resulted in 66 in situ measurements of K for each depth (as shown in Figure 1). All K measurements were made in the crop rows to avoid compaction due to wheel traffic, which would lower K values significantly by reducing total porosity and macroporosity [*Onofiok*, 1988]. The Guelph permeameter method described by *Reynolds and Elrick* [1986] was adopted for measuring the steady rates of recharge at 5 and 10-cm heads, and K values were calculated using the relationship based on Richard's analysis for steady state discharge from a cylindrical well in an unsaturated soil.

In addition to the Guelph permeameter technique, six undisturbed soil cores were taken from each of the 66 sites, with three replicates from each depth. Undisturbed soil cores (76 mm in diameter and 76 mm long) were collected with an Uhland core sampler for K measurements in the laboratory, using the constant head permeameter method [*Klute*, 1965]. For the lab method, 198 (3 × 66) cores were collected from 66 sites for each depth. After discarding few bad samples, 185 samples for the 15 cm depth and 188 samples for the 30 cm depth were analyzed. Details on the method of collecting undisturbed soil cores for K determination in the lab are given by *Kanwar et al.* [1989].

EXPERIMENTAL RESULTS

Table 1 and Figure 2 give the summary of the experimental K values obtained using the in situ Guelph permeameter and the laboratory constant head permeameter methods. The K values shown in Figure 2 for the laboratory method are the

TABLE 1. Summary of K Data Sets Based on 66 Sampling Sites Arranged on Two Transects Across the Field, Perpendicular to Each Other

Method Adopted	Lab* Depth 15 cm	Lab* Depth 30 cm	Field Depth 15 cm	Field Depth 30 cm
Number of observations	185	188	66	66
Average, cm/s	6.293×10^{-4}	8.737×10^{-4}	5.426×10^{-4}	3.923×10^{-4}
Maximum, cm/s	2.662×10^{-3}	2.163×10^{-3}	2.064×10^{-3}	1.813×10^{-3}
Minimum, cm/s	5.240×10^{-5}	3.037×10^{-5}	2.034×10^{-5}	1.822×10^{-5}
Standard deviation	5.664×10^{-4}	6.296×10^{-4}	4.414×10^{-4}	3.432×10^{-4}
Variance	3.208×10^{-7}	3.965×10^{-7}	1.948×10^{-7}	1.178×10^{-7}
Coefficient of variation, %	90.00	72.07	81.35	87.46

*These statistical parameters are based on average K (i.e., of three replicates).

arithmetic averages of three replicates collected from each site. On the average the constant head laboratory method provided higher K values than the Guelph permeameter method. Moreover, the standard deviations and coefficient of variations for K were generally higher for the laboratory method in comparison with the Guelph permeameter method. These differences between lab and field data could have been caused by macroporosity effects, experimental method effects, and/or sample volume effects. A study by *Lauren et al.* [1988] showed a large variation in K values due to sample volume used when the soil contained macropores. They found more accurate K estimates with larger soil samples. Our study contained a large number of macropores (wormholes and root channels) oriented nearly vertically within the top 30 cm of the soil. The wormholes and root channels were different in size and density at 15 and 30 cm depths because of differential growth and density of plant roots at different depths [*Singh et al.*, 1991].

In addition to the sample volume or macropore effects, the variation between the lab and Guelph permeameter methods might be compounded because of the inherent differences. The Guelph permeameter measures the composite of horizontal and vertical values for K under anisotropic conditions, whereas the lab method determines the vertical K values. Moreover, the K values measured by the Guelph permeameter are also affected because of smearing of the well wall, compaction, and air entrapment, which could also reduce the conductivity in comparison with the measured K values in the lab. For some soil cores we observed extremely high K values due to short-circuiting of water through the unexpectedly large number of continuous macropores (channels). Similar phenomena have been reported by *Lauren et al.* [1988] and *Kanwar et al.* [1989].

Spatial Analysis and Discussion

Robust-Resistant Approach for Semivariogram Development

Exploratory techniques [*Tukey*, 1977; *Velleman and Hoaglin*, 1981] are suitable for spatial analyses of soil properties using resistant (i.e., arithmetically stable) and robust (i.e., model stable) methods [*Hamlett et al.*, 1986; *Cressie and Horton*, 1987]. Incorporating resistant measures and robust ideas, the basic objective of exploratory data analysis techniques is to overcome the nonstationarity within the experimental data, which is a common occurrence under field conditions. Downweighting by a robust estimator [*Cressie and Hawkins*, 1980] or removal by resistant measures [*Tukey*, 1977] of any outliers present in a data set helps to achieve the stationarity conditions for the semivariogram development.

For the K data collected in this study a resistant technique (little affected by data outliers) was used to examine the spatial structure of K values in conjunction with geostatistics. Normal probability plots and plots of median against interquartile range squared were also developed to examine the data distribution and variance stationarity. The running median smoother approach [*Velleman and Hoaglin*, 1981, pp. 163] is simplified to a split-window median polish technique for our spatial analysis and is discussed in the following sections. A major finding is that while serving as an efficient smoothing tool, the median behaves more as a "solo representative" or "summary point" for the data set of a particular window.

Figure 2 shows normal probability plots of raw K data for two soil depths using two methods (i.e., in situ Guelph permeameter and laboratory constant head permeameter). These plots show a highly skewed distribution of K data. For the resistant analysis, stationarity of the variances against medians was checked. Because we matched our sampling grid design and expected soil clustering in the glacial till material (due to differential and incremental deposition of soil material during the process of formation and afterward), both transects were divided into a number of regular windows each having an equal number of sampling sites. Figure 3 shows the median of the windows and their interquartile range squared to inspect the stationarity of variance. This figure shows that the variance (interquartile range squared) is correlated with the median value, indicating the presence of nonstationarity in the variance. To remove the nonstationarity and nonnormality in the data sets, different transformations and resistant-based remediation techniques were tried.

K data were transformed to produce a nearly normal distribution (i.e., approximately symmetric, bell-shaped stem-and-leaf plot), and homogeneous variances [*Cressie*, 1985] using the "universal transformation principle." Different transformations were invoked to squeeze or spread the data set to obtain a more bell-shaped or Gaussian curve. Square root, cube root, and other power transformations [*Tukey*, 1977; *Cressie and Horton*, 1987] and scaled transformations [e.g., *Bresler et al.*, 1982] yielded good results in transforming the nonnormal data sets to nearly normal data sets. But the question arises about the stationarity of variance, which could not be assured by these transformations. Log_e transformation yielded fairly homogeneous variance (i.e., interquartile range squared) with respect to the median of windows across the transects (Figure 3) for K values at 15 cm depth (lab method) but did not show much improvement for K values at 30 cm depth. A comparison of Figure 2 illustrating raw K data with Figure 4 illustrating log-transformed K data and the χ^2 test (Table 2) clearly indicate that K values tend to be lognormally distributed. Although log transformation has nearly normalized the data set, the presence of local trends or regional clustering in the soil might be causing the nonstationarity. Therefore normalized data is assumed to follow the relation

$$Z(x) = \mu(x) + \varepsilon(x), \tag{6}$$

where $Z(x)$ denotes the log-transformed regionalized variable at location (x), $\mu(x)$ is a measure of central tendency, that is, deterministic drift of the variable at location (x), and $\varepsilon(x)$ is the random component at location (x) normally distributed with zero mean, which satisfies the second-order stationarity required for spatial analysis. All experimental K data were therefore log-transformed, and $\log_e K$ values were used for further analysis. But at the same time it is known that additivity principles are valid only on the same scale [*Cressie*, 1985]. Therefore it was decided to carry out the entire analysis with the data on log scale and to transfer the results to the original scale whenever required.

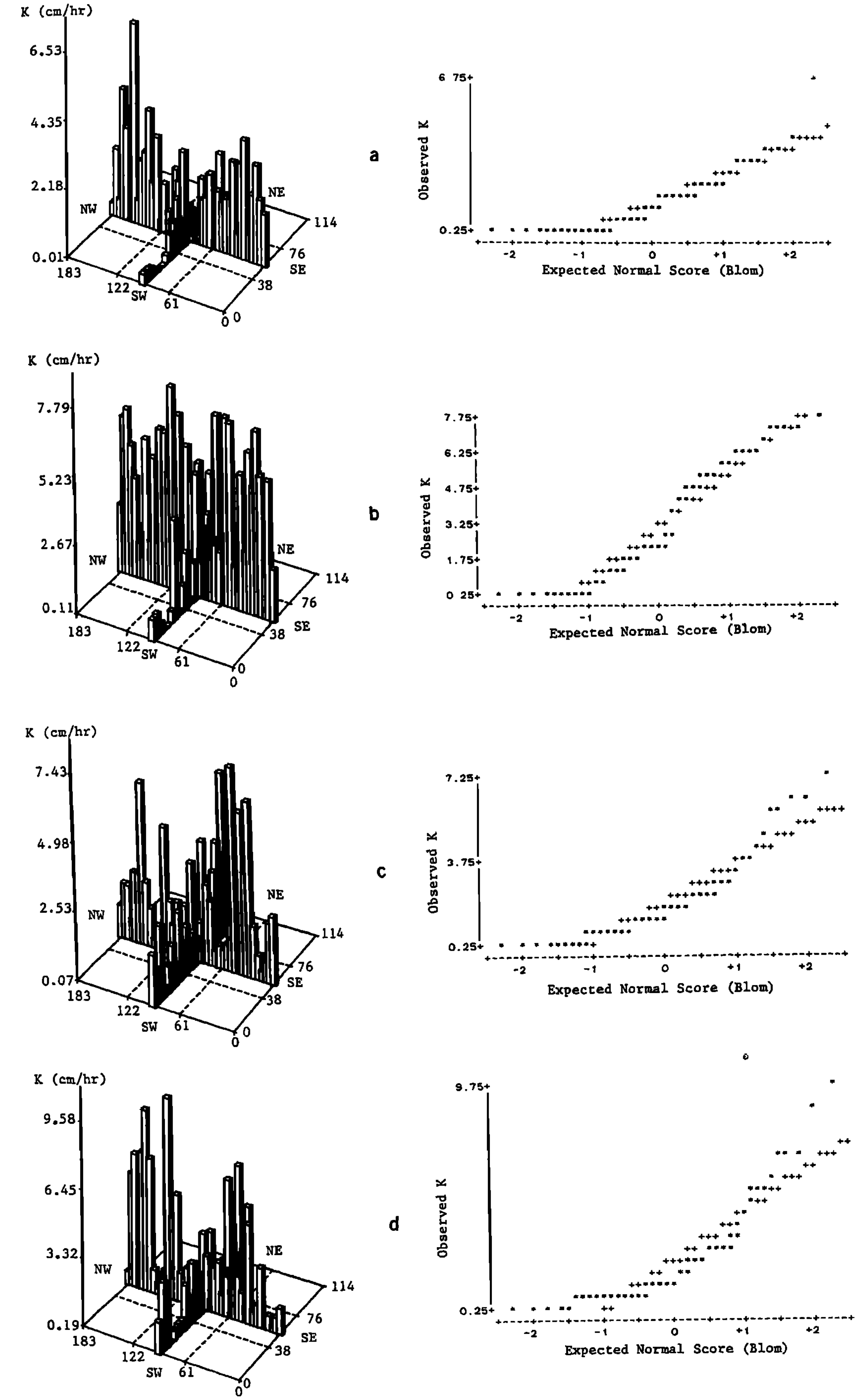


Fig. 2. Steady state K data: (*a*) 30 cm, field; (*b*) 30 cm, lab; (*c*) 15 cm, field; and (*d*) 15 cm, lab. Spatial distribution plots are on the left and normal probability plots are on the right.

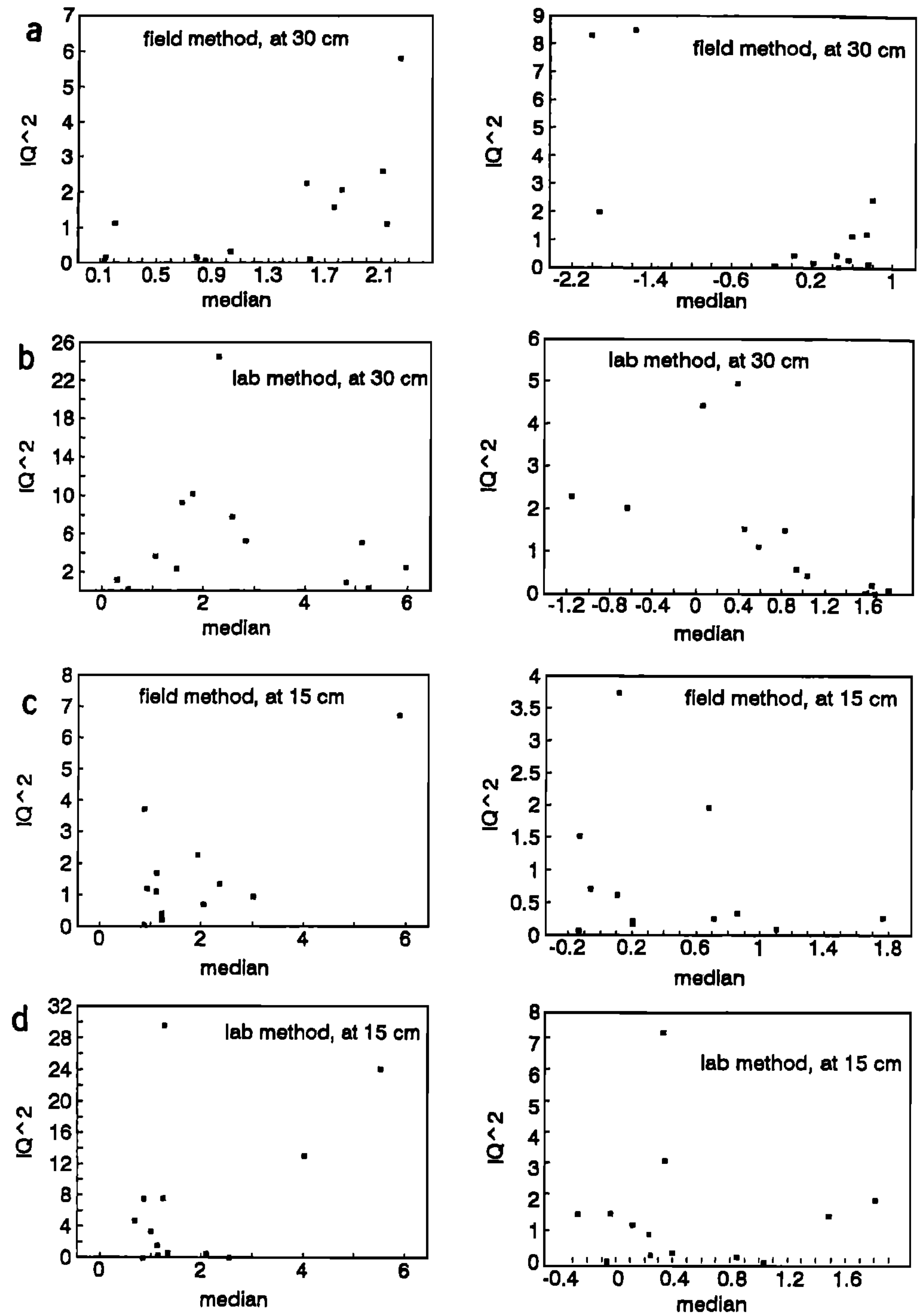


Fig. 3. Median-interquartile range squared plots for K data sets: raw data (left) and log-transformed data (right).

Semivariograms at 30 cm Depth

Experimental semivariograms based on $\log_e K$ values were developed and are presented in Figure 5. These two-dimensional mean isotropic semivariograms were based on all 66 log-transformed data (with wild outliers present). A robust estimator [*Cressie and Hawkins*, 1980], however, was used to curtail the effects of these outliers by downweighting. Strong positive spatial dependence was found for both in situ and lab methods at a depth of 30 cm under no-till conditions. Figures 5*c* and 5*d* show plots of $\bar{\gamma}(h)$ versus h. The dip in the lag range of 15 to 30 m may be an indication of some kind of short-scaled variation in K. It may by cyclic or clustered. Short-scale variation should not be confused with microheterogeneity of soil. Moreover, these semivariograms show an overall range much higher than these short-scale variational ranges. The lower "nugget effect" in comparison with the sill value in Figures 5*c* and 5*d* indicates that spatial structure dominates microheterogeneity in the soil. At the same time, moderately steeper slopes of these variograms signify the changes in K values, indicating moderately irregular, erratic, or discontinuous surfaces.

Directional semivariograms (γ_i) as shown in Figures 5*c*

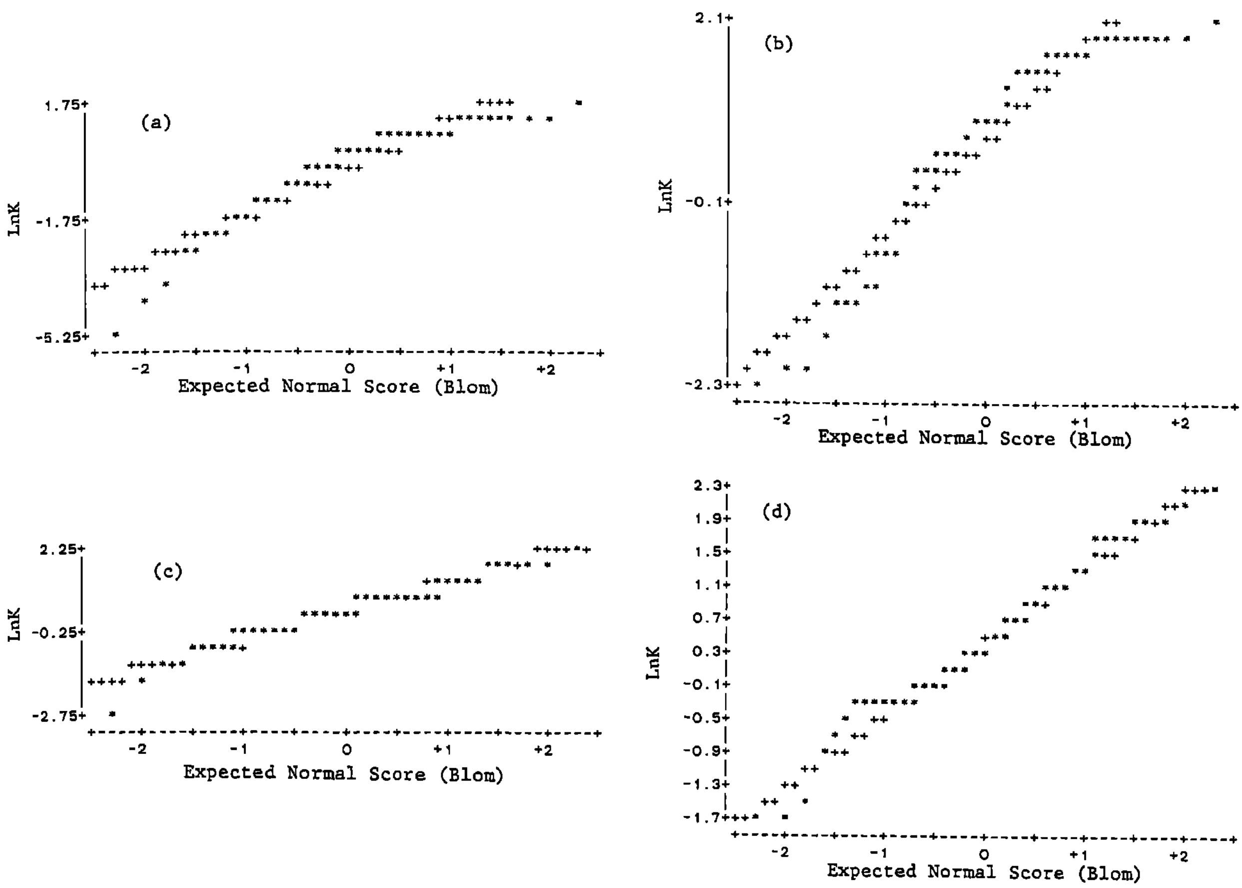


Fig. 4. Normal probability plots of log-transformed K data sets: (*a*) 30 cm, field; (*b*) 30 cm, lab; (*c*) 15 cm, field; and (*d*) 15 cm, lab.

and 5*d* at 30 cm depth were developed along the transects (NW-SE and NE-SW) and along the diagonal directions (N-S and E-W), with a tolerance of ±22.5°. The average semivariogram (γ^*) using the weighted average $[(1/\Sigma n_i)\Sigma_i n_i \gamma_i]$ was developed. All-directional mean isotropic variograms ($\bar{\gamma}$) compared well with average variograms (γ^*). But the directional semivariograms show new interesting behaviors. In both instances (laboratory and in situ) the main feature of directional variation is easily observed. Sill is maximum for γ_i in the NW-SE direction and minimal in the E-W direction, although the range remains approximately the same for all directions. Looking at Figures 5*c* and 5*d*, it is difficult to differentiate whether the difference between these directional variograms are due to the proportional effect or to anisotropicity indicating the underlying depositional process of glacial till. Looking at the semivariograms toward higher lag distances, one might assume that the phenomenon is proportional. By focusing the comparison near the origin, one might conclude that the phenomenon is indeed zonal anisotropy [*Journel and Huijbregts*, 1978, p. 181; *David*, 1977, p. 135], which may not be true because all measurements were made at the same depth (30 cm). Moreover, because the sampling scheme adopted was regular and on bisecting transects, the chances of clustered-sampling locations were eliminated, and such locations are the usual causes of "quasi-stationarity" producing a "proportional effect" in semivariogram estimates. Therefore it is difficult to determine the cause of the underlying process contributing to the spatial structure of K. The proportional effect, however, seems to be effecting more than the anisotropy effects, considering the nonstationarity of the log-transformed data due to soil clustering described earlier. Therefore all-directional mean isotropic semivariograms estimated using the entire K data set for both transects

TABLE 2. χ^2 Test of Normality for K and ln K

		K			ln K		
Method	Depth, cm	χ^2	Degrees of Freedom	P.L.	χ^2	Degrees of Freedom	P.L.
Lab	15	33.36	4	≪0.005	3.17	3	0.366
Lab	30	13.45	4	0.0093	11.3	3	0.011
Field	15	40.55	4	≪0.005	7.19	4	0.124
Field	30	19.67	3	≪0.005	6.94	3	0.072

P.L., level of significance.

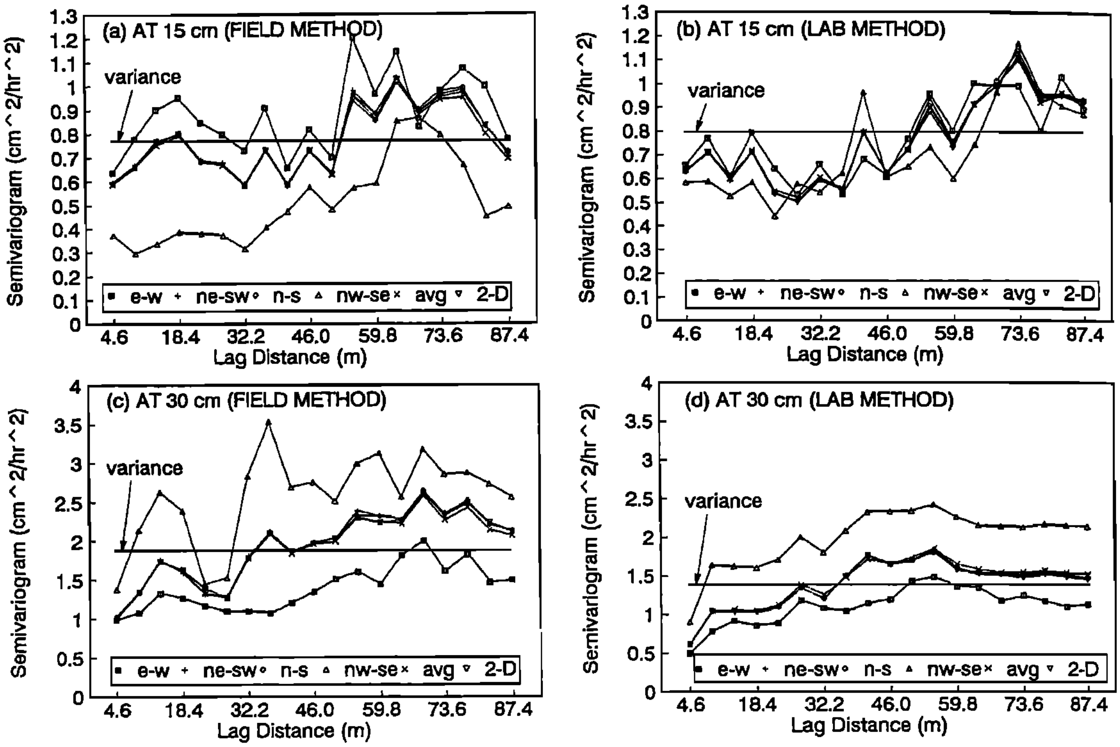


Fig. 5. Experimental robust semivariograms (directional, average, and two-dimensional mean isotropic).

represent the spatial structure of the till soil at 30 cm. The "short-scale variation," representing the clustering phenomenon, and the "large-scale variation," indicating soils of similar hydraulic properties, seem to have greater spatial correlation (i.e., smaller γ values) along the NE-SW transect than along the NW-SE transect. The orientation of maximum and minimum continuity along these directions suggests incremental deposition causing layered and overlapping soils.

Semivariograms at 15 cm Depth

Semivariograms for 15 cm depth (Figures 5*a* and 5*b*) were of dissimilar characteristics and dominated by white noise and trends. Even though semivariograms $\gamma(h)$ for the Guelph permeameter and lab methods did not match very well, both revealed a typical concave trend, and the one for lab measurements was more prominent. In these variograms the higher nugget effect versus sill is caused by random variability of "microheterogeneity" in comparison with structural variation, indicating a weak spatial dependence. Possible reasons for this variation are farm traffic and freezing and thawing phenomena which break the soil structure unevenly at the surface of no-till soil. *Hamlett et al.* [1986] observed a similar phenomenon for their soil water tension study in no-till plots, which was due to variability in soil surface residue cover and soil pore continuity. From this evidence it can be concluded that the no-till plots lack good spatial structure at the surface soil layer of 0–15 cm.

Theoretical Model Fitting

Usually, the forecasting of variogram models facilitates follow-up spatial studies. Therefore an effort was made to generalize the structural trends by fitting experimental semi-

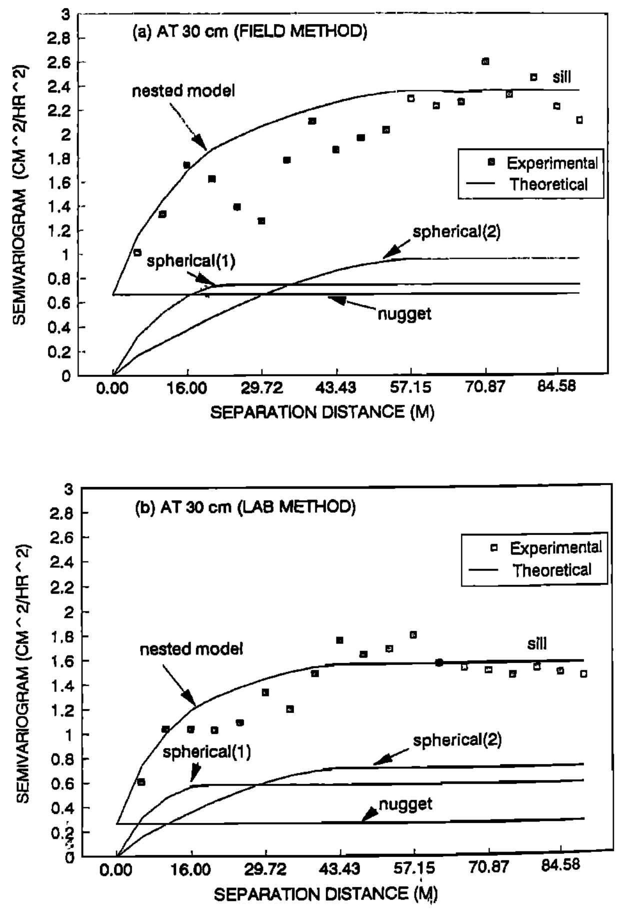


Fig. 6. Theoretical models fitted to the experimental two-dimensional mean isotropic semivariograms for ln K at 30 cm depth; nested structure of nugget and two spherical models with different sills and ranges.

TABLE 3. Theoretical Models Fitted to Two-Dimensional Mean Isotropic Semivariograms for ln K Data Sets

Depth, cm	Method	Models	Applicable Range, m
30	lab	$\gamma(h) = 0.265 + 0.583(1.5h/18 - 0.5h^3/18^3) + 0.715(1.5h/46 - 0.5h^3/46^3)$	$h < 18$
		$\gamma(h) = 0.265 + 0.583 + 0.715(1.5h/46 - 0.5h^3/46^3)$	$18 \le h < 46$
		$\gamma(h) = 0.265 + 0.583 + 0.715$	$h \ge 46$
		$\gamma(0) = 0$	
15	field	$\gamma(h) = 0.663 + 0.742(1.5h/23 - 0.5h^3/23^3) + 0.954(1.5h/60 - 0.5h^3/60^3)$	$h < 23$
		$\gamma(h) = 0.663 + 0.742 + 0.954(1.5h/60 - 0.5h^3/60^3)$	$23 \le h < 60$
		$\gamma(h) = 0.663 + 0.742 + 0.954$	$h \ge 60$
		$\gamma(0) = 0$	

variograms with standard theoretical models. The fitted theoretical models were found useful in analyzing and interpreting our results of the split-window-based resistant approach.

Theoretical models were fitted for the experimental variograms at 30 cm depth by the trial and error approach and were validated using a simple point-kriging approach (see Figures 6*a* and 6*b*). The developed theoretical models for the observed K data had a nested structure with three distinct components. A small "nugget effect" (C_0) indicates inherent "microheterogeneity" of soil samples. A spherical model with sill (C_1), which fabricates the structure of the soil within a lag distance of about 20 m, could be termed a "short-scale variation." The third component, modeled with another spherical model with sill (C_2), indicating "large-scale variations," had an overall range of spatial dependence for K up to 60 m (in situ method). An exponential model with the same sill and range, however, showed equally good fit as the spherical one but showed the typical asymptotic behavior. Thus the spherical one was preferred over the exponential one. The overall nested structure of the models and their characteristic parameters are presented in Tables 3 and 4. Comparison of these models for two different K-measuring techniques showed excellent consistency in their trends even though some variations in their parametric values were observed. The three major cross-validation criteria (KAE, KRMSE, and KMSE) estimated are shown in Table 5. Values of KAE, KRMSE, and KRMSE were close enough to their recommended optimum. Correlation coefficients (R^2) between the regionalized variable and the kriged estimate were reasonably good at 0.64 and 0.58 for lab and in situ methods, respectively, ensuring the nested model as a good fit (Figure 7).

Summarily, the semivariograms of log-transformed data $Z(x)$ for 30 cm depth show cyclic or clustering behavior at about 20-m lag distance, thereby indicating a nonrandom shift for both measuring techniques. At 15 cm depth for K values measured with the Guelph permeameter the normal probability plot and the semivariogram estimators confirm the effect of random variability contributing toward the "nugget effect." The semivariogram estimators at 15 cm depth for lab measurements (Figure 5*b*) showed, however, a typical linear drift in the NW-SE direction. Handling this kind of cyclic or clustering pattern and/or directional trend and coming up with model parameters is not a trivial task [*David*, 1977, p. 266; *Journel and Huijbregts*, 1978, p. 313]. *Webster and Burgess* [1980], *Yost et al.* [1982], and other researchers have discussed methods of handling drift (or detrending the data) by modeling it and using up to second-degree polynomials. On the other hand, *Hamlett et al.* [1986] adopted the nonparametric median polish approach [*Tukey*, 1977] to remove the drift along all grid directions and found it a better and more economical approach than the former because the nature of data or residuals can be visualized after every operation. This approach could support the spatial analysis by judging the normality of data and stationarity of variance and of median and by revealing the presence or removal of drift or clusters, resulting in interpretable semivariogram estimators $\gamma(h)$.

Split-Window Median Polish

Following semivariogram development, an exploratory approach of "split-window median polish" was used to analyze and interpret the behavior of the $\log_e K$ data sets. This approach was found suitable for analyzing the cyclic or clustering behavior of the data sets. Both the NE-SW and NW-SE transects were split into a number of spans or windows of equal lengths (and equal numbers of sampling sites because of the regular sampling pattern). Medians of these windows were estimated. Window lengths having odd three (13.8 m), five (23 m), and seven (32.2 m) numbers of sampling points were chosen to calculate the medians of the windows of K data. Windows of up to a maximum of seven sites (i.e., 32.2 m) were considered, because the previous estimated semivariograms for the log-transformed K values at 30 cm depth showed a clustering behavior in the spatial structure at a lag distance of about 18 to 23 m. The first

TABLE 4. Summary of Spatial-Dependent Parameters of ln K at 30 cm Depth for the Glacial Till Soil

Method Adopted	Depth, cm	Nugget Effect (C_0)	Structural Component: Model 1 C_1	Structural Component: Model 2 C_2	Sill C ($C_0 + C_1 + C_2$)	C_0/C, %	Range: Model 1, m	Range: Model 2, m	Variance
Lab	30	0.265	0.583*	0.715*	1.563	17	18	46	1.431
Field	30	0.663	0.742*	0.954*	2.359	28	23	60	1.871

*Spherical.

TABLE 5. Values of Cross Validation Criteria for the Nested Models of ln K at 30 cm Depth

Method	Depth, cm	KAE	KRMSE	KMSE/SD	Search Radius, m/Neighborhood Size	R^2
Lab	30	−0.0033	1.0556	0.8963/1.196	46/10	0.64
Field	30	−0.0173	1.0041	1.1127/1.368	60/13	0.58

iteration of the median polish approach [*Tukey*, 1977] for each window was performed to account for the clustering effect of K property. Residuals were calculated by subtracting the median of respective windows from the regionalized variable at each site as

$$R(x) = Z_i(x) - \tilde{Z}_i \qquad i = 1, 2, \cdots, N, \tag{7}$$

where $R(x)$ denotes the residual value at location (x), $Z_i(x)$ is the log-transformed K data and belongs to window (i), and $\tilde{Z}_i$ indicates the median of window i. The odd number of data values left at the end of the transect (which could not be accommodated in the windows of specified lengths) were averaged out or taken as such if they were left alone. Stem-and-leaf plots and normal probability plots of these residuals $R(x)$ were developed and examined visually. The best sets of residuals were obtained with a window width of 23 m (of five sites) with nearly normal distribution. Stem-and-leaf plots and normal probability plots are shown in Figure 8 for 23-m windows. Moreover, the medians of these residuals for all the windows across the transects were zero irrespective of interquartile range squared, which satisfies the variance and median stationarity rule for semivariogram development.

Median-polished residual values were used for semivariogram estimation and are plotted in Figure 9. Instead of achieving better variograms with better structure, all appeared to exhibit the pure "nugget effect." However, when plots were examined of the window median across the transects (as shown in Figure 10 for NE-SW and NW-SE transects), some interesting features were discovered. The plots for 30 and 15 cm depth (Figures 10*a*–10*d*) show that the spatial structure lies in the median of the windows, indicating structural variation (i.e., regular variation of the median from window to window and clustering of soil of similar hydraulic properties inside the window, with few exceptions. Comparing the plots of medians (Figure 10) with the semivariograms drawn for log-transformed K values before median polishing (Figure 5) could reconfirm our results in terms of range of "short-scale" and "large-scale" variations. Examining these figures, it can also be judged that the overall range (large-scale variation) of soils of predictable K at 30 cm depth is of about three window lengths of 69 m (measured in situ) and about two window lengths of 46 m (measured in the lab). That reconfirms the overall spatial range found from the semivariogram analysis. Moreover, each window of 23 m length would represent soil of similar K value, indicating short-scale variation. Therefore when medians were subtracted from the raw data, the structural components were removed from the data set, leaving behind the "nugget effect" in the residuals, which resulted in the structureless semivariograms, as shown in Figure 9. Therefore the open-ended question, Is stationarity of regionalized variable a critical criterion for semivariogram estimation in this type of clustered soil?, may be posed at this moment. Interestingly, at 30 cm depth, both in situ and lab semivariogram estimators, as well as the medians across the transects, showed consistency in their trends even though some differences were observed in their sills and overall range of influence, which may have been caused by the basic difference between the two techniques.

In the plots for 15 cm depth, medians (Figures 10*c* and 10*d*) are dominated by white noise and a NW-SE drift matching the structureless semivariograms of the residuals (Figures 9*a* and 9*b*), indicating no apparent large-scale structure in the original data sets of K values for the surface layer (0–15 cm). Moreover, comparison of semivariograms at 15 cm depth (lab method), for log-transformed K data (Figure 5*b* with Figure 9*b* for median-polished residuals),

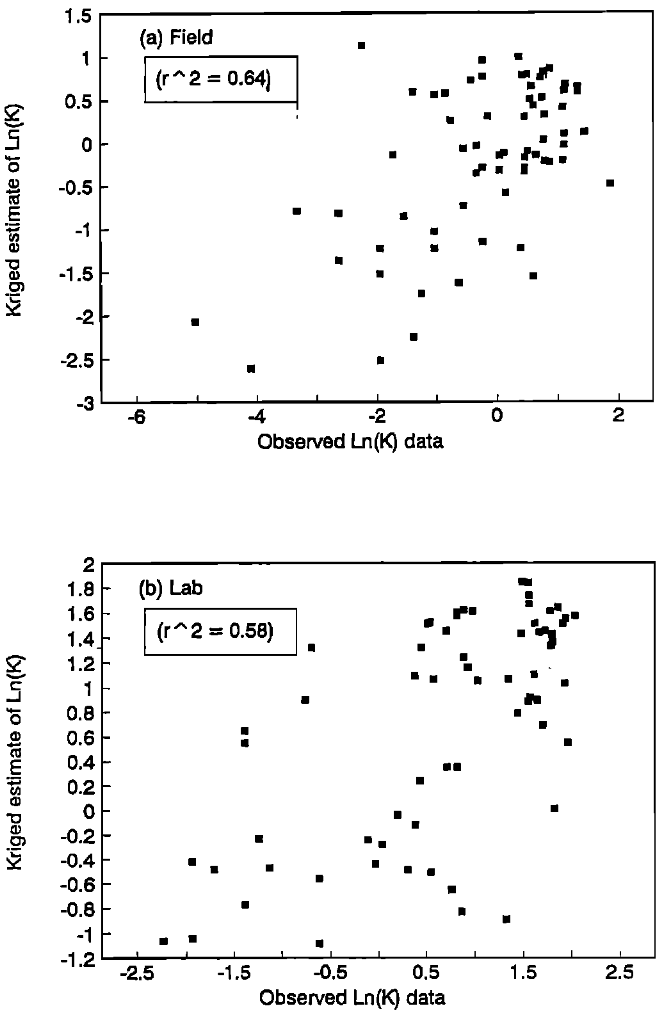
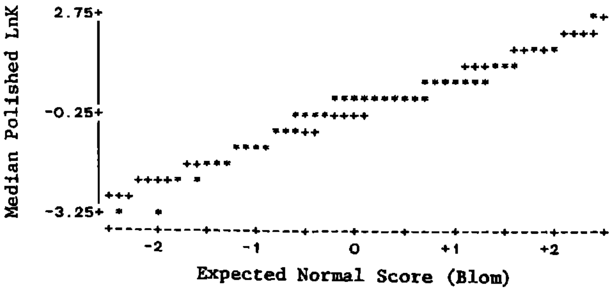


Fig. 7. Scatter diagrams of log-transformed K data versus kriged estimates based on the nested model at 30 cm depth.

```
STEM LEAF
   2 5
   2 0
   1 7
   1 0133
   0 555667789
   0 11222234444
  -0 431110000000000000000
  -0 9986
  -1 433200
  -1 8875
  -2 31
  -2
  -3 10
     ----+----+----+----+--
```

a




```
STEM LEAF
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  18
  16
  14 7
  12 78
  10 001247
   8 7
   6 1122
   4 18
   2 3694
   0 112578
  -0 65118865410000000000000
  -2 9840
  -4 0
  -6 40
  -8 62
 -10
 -12 92
 -14 7562
 -16
 -18
 -20 7
 -22 0
     ----+----+----+----+---
 MULTIPLY STEM.LEAF BY 10**-01
```
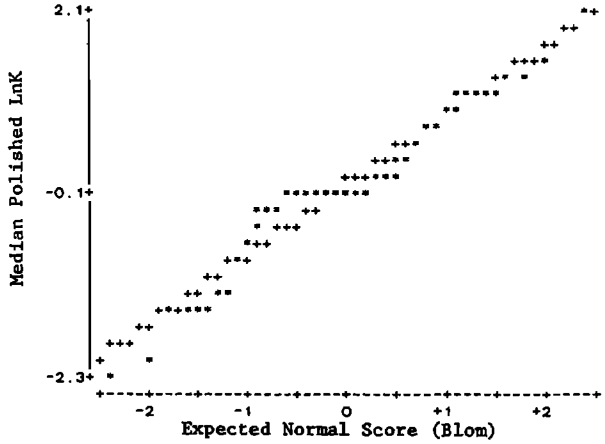
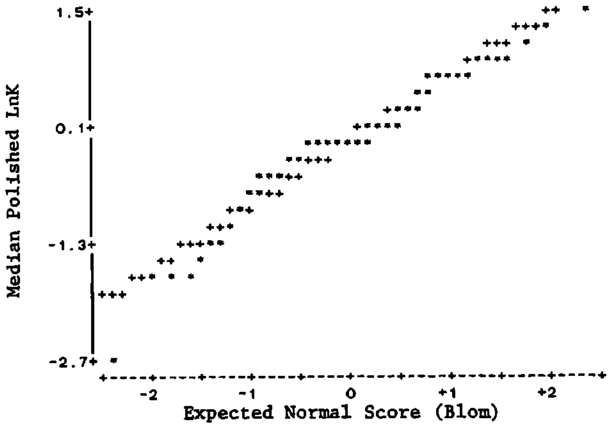

b




```
STEM LEAF
  14 1
  12 01
  10 0
   8 503
   6 1389927
   4 58
   2 34512
   0 2289128
  -0 54330000000000000
  -2 30440
  -4 89875
  -6 33
  -8 41
 -10 9
 -12 94
 -14 0
 -16 593
 -18
 -20
 -22
 -24
 -26 3
     ----+----+----+----+
 MULTIPLY STEM.LEAF BY 10**-01
```

c




```
STEM LEAF
  18 2
  16 22
  14 0453
  12 388
  10 0
   8 57
   6 6
   4 397
   2 479016
   0 4569
  -0 997630700000000000000
  -2 87311
  -4 93
  -6 00
  -8 8
 -10 6213
 -12 75
 -14
 -16
 -18 206
     ----+----+----+----+-
 MULTIPLY STEM.LEAF BY 10**-01
```

d

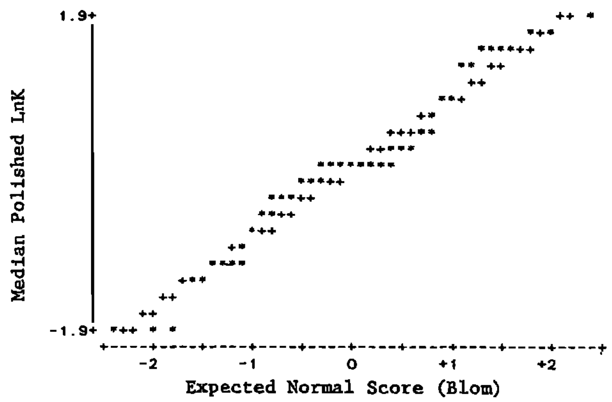


Fig. 8. Stem-and-leaf plots (left) and normal probability plots (right) of ln K residuals after split-window median polish: (*a*) 30 cm, field; (*b*) 30 cm, lab; (*c*) 15 cm, field; and (*d*) 15 cm, lab.

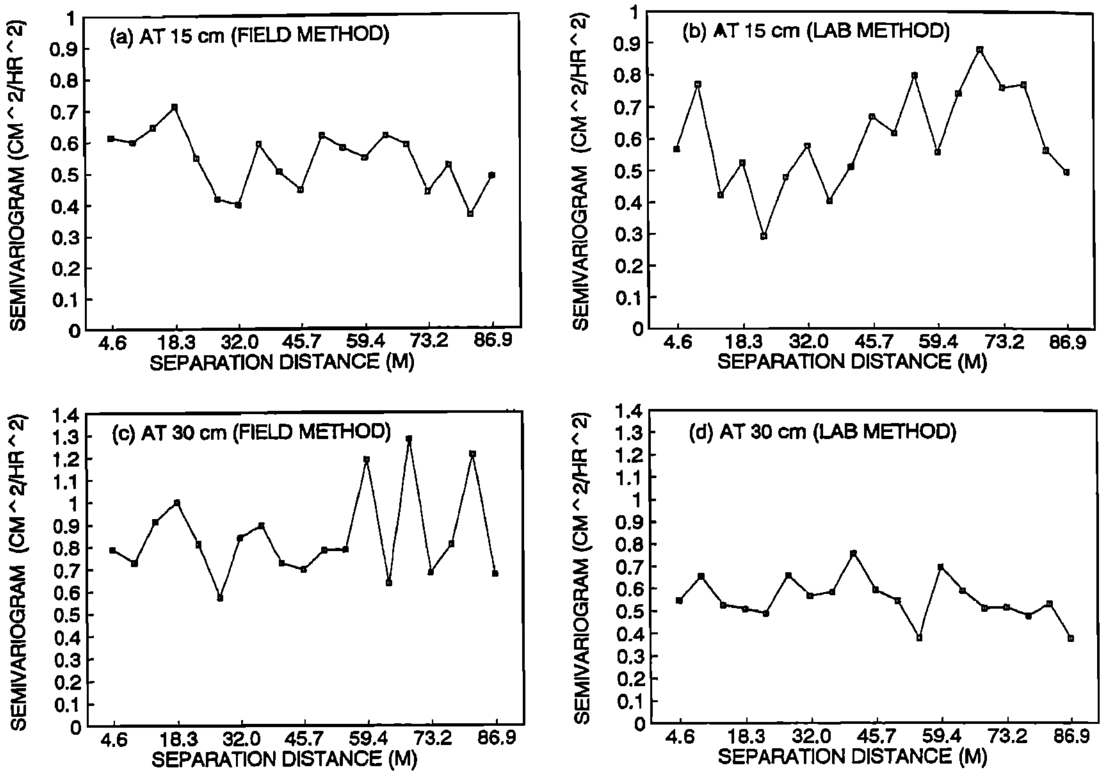


Fig. 9. Robust semivariograms of the residuals following split-window median polish.

reconfirms the presence of a drift in the medians of the windows. Thus it attributes the median a "solo representative" or "summary point" of the window when the structure can be best described as a "single-window structure."

Split-Window Median Polish Versus Universal Kriging

Universal kriging [*Matheron*, 1971; *Journel and Huijbregts*, 1978; *Webster and Burgess*, 1980] was performed on lab 15-cm data to give a qualitative comparison with split-window median polish to remove the local drift. Least square fits (simple regression) of the log-transformed K values versus X-Y coordinates of the field indicated a reasonable correlation between the X axis (NW-SE) and the K values. As reported by previous researchers, drift of an order higher than quadratic is almost never needed in universal kriging. Linear and quadratic drifts were tested by trial and error in conjunction with different linear and nugget variograms to represent the residuals. From the cross-validation criteria in this instance we did not achieve anything significant for quadratic trend over the linear trend. Therefore in order to avoid needed detail, linear trend was considered to be the best approximation. The experimental variograms (up to eight lags) were almost falling on the best fit linear model for all directions. Universal kriging was therefore performed with a moving neighborhood (search radius) of eight lag distances. Semivariograms of the residuals after removing the linear drift showed a limited or absent spatial relation for the laboratory K data set (Figure 11). Such a behavior is often referred to as "nugget effect." These changes indicate that a higher rate of variability and smaller zone of influence resulted from detrending. As expected, however, detrending followed by residual semivariogram development decreased the estimate of bias (sum of residuals: original data minus kriged estimate) but not significantly. Furthermore, comparison of Figures 11 and 9*b* shows the close match of results obtained by both the methods. It assures that the split-window median polish is an equally suitable and much easier approach for the spatial analysis of clustered soils.

SUMMARY AND CONCLUSIONS

Spatial structure for saturated hydraulic conductivity (K) of a glacial till material under no-tillage condition was examined for two depths with two K measuring techniques. Evidence of nonstationarity in K data pose problems on the reliability of semivariogram estimators. Analysis of data before developing the semivariogram was discussed. Log transformation followed by an economical resistant data analysis using split-window median polishing technique was used to remove the median and variance nonstationarity from a data set generating valuable semivariogram estimators for the interpretation of the structural variability.

A robust estimator [*Cressie and Hawkins*, 1980] was used to accommodate the contaminating outliers. Semivariograms estimated for both methods of K measurements were found to have close similarity for 30 cm depth. Good spatial structure was observed (short-scale variability) within a lag distance of 20 m for determining K values of the glacial till soil. Beyond this range a more clustering effect in K was observed with an overall range (large-scale variability) of 60 m (in situ method). Spatial structure of K was modeled using the nested structure of three different components, namely, random variability due to soil "microheterogeneity",

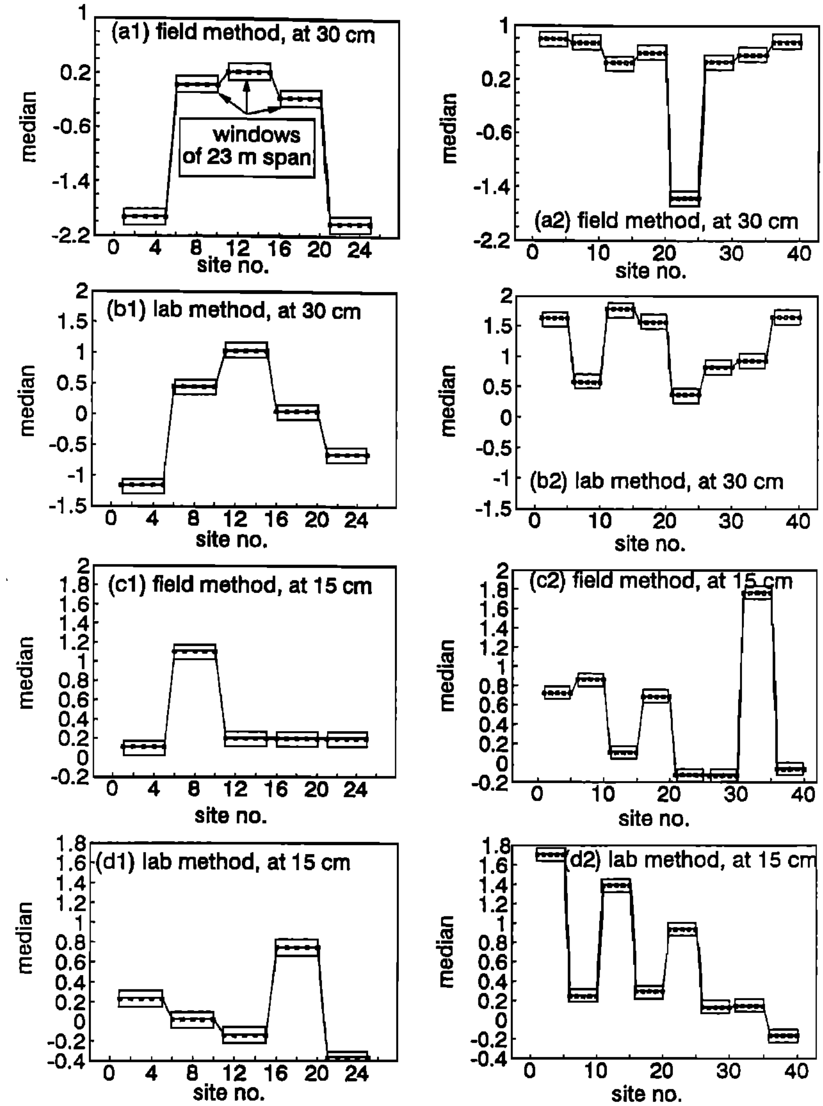


Fig. 10. Medians of ln K as "solo representative" of split windows across the transects NE-SW (left) NW-SE (right).

"short-scale variability", which may be due to clustering of till material by differential deposition, and "large-scale variability" due to the soil of the same type or origin. The nugget effect, and two spherical models, were used in the above in

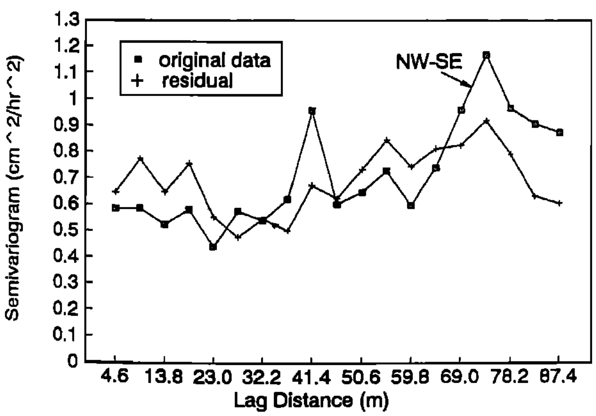


Fig. 11. Semivariograms of ln K at 15 cm depth (lab method) before and after a linear drift was removed by universal kriging.

order to fabricate the overall structure of the till material. Further exploratory data analysis exposed an interesting fact indicating that spatial structure of the clustered soil lies in their medians, which may be called "solo representatives" or "summary points" of clusters. This clustering phenomenon is due to differential deposition of soil layers by glacial drifts during its formation or subsequent incremental deposition due to wind drifts.

Semivariogram estimators for in situ K values at 15 cm depth under the no-till condition did not exhibit any large-scale structure in addition to weak small-scale structure. Variability is dominated by the heterogeneity in the soil. Reasons for this behavior may be due to uneven breaking of soil structure due to freezing and thawing at this shallow layer. Moreover, a typical directional trend was found for both in situ and lab measurements of K. This trend became more prominent in the medians of the windows across the NW-SE transect. Split-window median polish was found to be a useful tool, for clustered soils, in performing a reliable spatial analysis, resulting in more realistic structural estimators for better interpretation of K data.

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REFERENCES

Bresler, E., G. Dagan, and R. J. Hanks, Statistical analysis of crop yield under controlled line-source irrigation, *Soil Sci. Soc. Am. J.*, *46*, 841–847, 1982.

Burgess, T. M., and R. Webster, Optimal interpolation and isarithmic mapping of soil properties, I, The semivariogram and punctual kriging, *J. Soil Sci.*, *31*, 315–331, 1980.

Clark, I., *Practical Geostatistics*, 129 pp., Applied Science Publishers, London, 1979.

Cressie, N. A. C., Towards resistant geostatistics, in *Geostatistics for Natural Resources Characterization*, edited by G. Verly et. al., pp. 21–24, D. Reidel, Hingham, Mass., 1984.

Cressie, N. A. C., When are relative variograms useful in geostatistics?, *J. Math. Geol.*, *17*, 693–702, 1985.

Cressie, N. A. C., Kriging nonstationary data, *J. Am. Stat. Assoc.*, *81*, 625–634, 1986.

Cressie, N. A. C., and F. Glonek, Median based covariogram estimators reduce bias, *Stat. Prob. Lett.*, *2*, 299–304, 1984.

Cressie, N. A. C., and D. M. Hawkins, Robust estimation of the variogram, *J. Int. Assoc. Math. Geol.*, *12*, 115–125, 1980.

Cressie, N. A. C., and R. Horton, A robust-resistant spatial analysis of soil water infiltration, *Water Resour. Res.*, *23*(5), 911–917, 1987.

David, M., *Geostatistical Ore Reserve Estimation*, 364 pp., Elsevier, New York, 1977.

Dreimanis, A., Tills: Their origin and properties, Glacial till: An inter-disciplinary study, *Spec. Publ. 12*, edited by R. F. Legget, pp. 11–49, Royal Soc. of Canada, Ottawa, 1976.

Gajem, Y. M., A. W. Warrick, and D. E. Myers, Spatial dependence of physical properties of typic Torrifluvent soil, *Soil Sci. Soc. Am. J.*, *45*, 709–715, 1981.

Gambolati, G., and G. Volpi, Groundwater contour mapping in Venice by stochastic interpolators, 1, Theory, *Water Resour. Res.*, *15*(2), 281–290, 1979.

Grundy, W. D., and A. T. Miesch, Brief description of STATPAC and related statistical programs for the IBM personal computers, *U.S. Geol. Surv. Open File Rep. 87-411-A*, 1987.

Hamlett, J. M., R. Horton, and N. A. C. Cressie, Resistant and exploratory techniques for use in semivariogram analysis, *Soil Sci. Soc. Am. J.*, *50*, 868–875, 1986.

Horowitz, J., and D. Hillel, A critique of some recent attempts to characterize spatial variability, *Soil Sci. Soc. Am. J.*, *47*, 614–615, 1983.

Journel, A. G., and Ch. J. Huijbregts, *Mining Geostatistics*, 600 pp., Academic, New York, 1978.

Kanwar, R. S., J. L. Baker, and D. G. Baker, Tillage and split N fertilization effects on subsurface drainage water quality and corn yield, *Trans. ASAE*, *31*(2), 453–460, 1988.

Kanwar, R. S., H. A. Rizvi, M. Ahmad, R. Horton, and S. J. Marley, Measurement of field-saturated hydraulic conductivity by using Guelph and velocity permeameters, *Trans. ASAE*, *32*(6), 1979–1986, 1989.

Kanwar, R. S., C. J. Everts, and C. F. Czapar, Use of adsorbed and non-adsorbed tracers to study the transport of agricultural chemicals to shallow groundwater, paper presented at the International Symposium on Tropical Hydrology, San Juan, Puerto Rico, 1990*a*.

Kanwar, R. S., J. L. Baker, R. Horton, L. Jones, R. L. Handy, and L. Lutenegger, Annual progress report of the aquitard/till hydrology project, dep. of Agric. Eng., Agron., and Civ. Eng., Iowa State Univ., Ames, 1990*b*.

Klute, A., Laboratory measurements of hydraulic conductivity of saturated soil, in *Methods of Soil Analysis*, part 1, *Agronomy*, vol. 9, edited C. A. Black et al., pp. 253–261, American Society of Agronomy, Madison, Wis., 1965.

Lauren, J. G., R. J. Wagenet, J. Bouma, and J. H. M. Wosten, Variability of saturated hydraulic conductivity in a Glossaquic Hapludalf with macropores, *Soil Sci.*, *145*, 20–28, 1988.

Lutenegger, A. J., T. J. Kemmis, and G. R. Hallberg, Origin and properties of glacial till and diamictions, in *ASCE Geotechnical Division Special Publication on Geological Environment and Soil Properties, ASCE Geotechnical Division Convention, Houston TX, Oct. 17–21*, pp. 310–331, American Society of Civil Engineers, New York, 1983.

Matheron, G., Principles of geostatistics, *Econ. Geol.*, *58*, 1246–1266, 1963.

Matheron, G., *The Theory of Regionalized Variables and its Applications*, 211 pp., Centre de Morphologie Mathématique, Ecole des Mines, Fontainebleau, France, 1971.

Oliver, M. A., and R. Webster, Semi-variograms for modelling the spatial pattern of landform and soil properties, *Earth Surf. Processes Landforms*, *11*, 491–504, 1986.

Onofiok, O. E., Spatial and temporal variability of some soil physical properties following tillage of a Nigerian Paleustult, *Soil Tillage Res.*, *12*, 285–298, 1988.

Reynolds, W. D., and D. E. Elrick, A method for simultaneous in-situ measurement in the vadose zone of field-saturated hydraulic conductivity, sorptivity and the conductivity-pressure head relationship, *Ground Water Monit. Rev.*, *6*, 84–89, 1986.

Russo, D., A geostatistical approach to solute transport in heterogeneous fields and its application to salinity management, *Water Resour. Res.*, *20*(9), 1260–1270, 1984.

Russo, D., and E. Bresler, Soil hydraulic properties as stochastic processes, II, Errors of estimates in a heterogeneous field, *Soil Sci. Soc. Am. J.*, *46*, 20–26, 1982.

Sharma, M. L., R. J. Luxmoore, R. DeAngelis, R. C. Ward, and G. T. Yeh, Subsurface water flow simulated for hill slopes with spatially dependent soil hydraulic characteristics, *Water Resour. Res.*, *23*, 1523–1530, 1987.

Singh, P., R S Kanwar, and M. L. Thompson, Measurement and characterization of macropores using AUTOCAD and automatic image analysis, *J. Environ. Qual.*, *20*, 289–294, 1991.

Springer, E. P., and T. W. Cundy, Field-scale evaluation of infiltration parameters from soil texture for hydrologic analysis, *Water Resour. Res.*, *23*, 325–334, 1987.

Terzaghi, K., and R. B. Peck, *Soil Mechanics in Engineering Practice*, 2nd ed., John Wiley, New York, 1967.

Tukey, J. W., *Exploratory Data Analysis*, Addison-Wesley, Reading, Mass., 1977.

United States Department of Agriculture, Soil survey of Boone County, Iowa Agric. Home Econ. Exp. Stn., Ames, Iowa, 1984.

Vauclin, M., S. R. Vieira, R. Bernard, and J. L. Hatfield, Spatial variability of surface temperature along two transects of a bare soil, *Water Resour. Res.*, *18*(6), 1677–1686, 1982.

Vauclin, M., S. R. Vieira, G. Vachaud, and D. R. Nielsen, The use of cokriging with limited field soil observations, *Soil Sci. Soc. Am. J.*, *47*, 175–184, 1983.

Velleman, P. F., and D. C. Hoaglin, *Applications, Basics, and Computing of Exploratory Data Analysis*, 354 pp., Duxbury, Boston, Mass., 1981.

Webster, R., Quantitative spatial analysis of soil in the field, *Advances in Soil Science*, vol. 3, edited by B. A. Stewart, pp. 1–70, Springer Verlag, New York, 1985.

Webster, R., and T. M. Burgess, Optimal interpolation and isarithmic mapping of soil properties, III, Changing drift and universal kriging, *J. Soil Sci.*, *31*, 505–524, 1980.

Yost, R. S., G. Uehara, and R. L. Fox, Geostatistical analysis of soil chemical properties of large land areas, I, Semivariograms, *Soil Sci. Soc. Am. J.*, *46*, 1028–1032, 1982.

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